Optimum Equipment Maintenance/Replacement Policy Part 2. Markov Decision Approach

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This is the second article on the subject of Optimum Equipment Maintenance and/or Replacement Policy which employs the optimization technique called Markov Decision Process. In the first article, dynamic programming was utilized as an alternative optimization technique to determine an optimal policy over a given time period. According to a joint effect of the probabilistic transition of states and the sequence of decision making, the optimal policy is sought such that a set of decisions optimizes the long-run expected average cost (or profit) per unit time. Provision of an alternative measure for the expected long-run total discounted cost is also considered. A computer program based on the concept of the Markov Decision Process was developed and tested. The program code listing, the statement of a sample problem, and the computed results are presented in this report.

I. Introduction

In the first article (TDA Progress Report 42-66: September and October 1981), an optimal decision-making policy utilizing the dynamic programming technique was presented. The aim was to make optimal decisions, over a finite number of time periods, regarding the equipment maintenance and/or replacement for a given system.

When a system is required to be existing indefinitely, a best operation policy which gives the optimal long-run cost (or profit) may be estimated by successive approximations with dynamic programming techniques, providing a very large number of time periods is assumed. However, there is no way of knowing when to terminate the successive approximations; there is no procedure for deciding how large a number of time periods is sufficient.

This report presents another decision-making technique to obtain a long-run optimal policy utilizing the Markov Decision Process Concept. The optimal policy is evolved over time periods according to the joint effect of the probabilistic transition of the condition of the system and the sequence of decision making. It is assumed that for a system under consideration, there exists a policy at any time period. The system changes to a new state at the next time period according to a known probability after a decision is made at the present time period and at the present state.

In such decision making, different transition matrixes result, corresponding to the decisions made at each observed time period. Accordingly, a change of state as well as the associated value of cost (or profit) of the system in the next time period is governed by the transition matrix. The optimal

is sought such that the set of decisions made will optimize the long-run expected average cost (or profit) per unit time period.

However, in systems involved with a long time-horizon, the changing time value of money is of importance, and the expected long-run total discounted cost (or profit) should be determined with respect to a specific discount factor. The discount factor a is the present value of one unit money in one time period, expressed as:

$$a = \frac{1}{1+i} \tag{1}$$

where i is the rate of return on the money for one time period. After M periods, a unit of money will be worth a^{M} .

Derivation of mathematical equations, discussion of the policy-improvement computational algorithm, and a sample problem are presented in the following sections. A computer program employing the discussed algorithm is given in Appendix A.

II. Theoretical Model

Brief descriptions of the Markov Decision Process and the necessary equations are discussed as follows. More detailed derivations of the equations may be found in Refs. 1, 2.

Consider a system which at a particular time period (t=1, 2, 3, ...) is in one state i out of M states. The system changes from one of these admissible states, i, to another state, j, ruled by a transition matrix, $P = (p_{ij})$. The elements, p_{ij} , are defined as the probabilities the system is in state j at t, given that it was in state i at (t-1). Further, it is assumed that the transition matrix P is not time-dependent.

Let $q_{ij}(k)$ be the expected cost (or profit) incurred when the system, which originally is in state i, changed after a decision k is made to a state j at the next observed time period. Then,

$$C_{ik} = \sum_{j=1}^{M} q_{ij}(k) p_{ij}(k)$$
 (2)

where C_{ik} is the cost incurred at the first observed time period as a result of the current state i and the decision $D_i(R) = k$ when operating under policy R.

By introducing $V_i^N(R)$ as the total expected cost of a system starting in state i (at the first observed time period) and

evolving for N time periods following a policy R, the recursive equation can be written as

$$V_i^N(R) = C_{ik} + \sum_{j=1}^{M} p_{ij}(k) V_j^{(N-1)}(R)$$
 (3)

The second term on the right-hand side of Eq. (3) is the total expected cost of the system evolving over the remaining (N-1) time periods.

Let g(R) be the long-run expected average cost per unit time following a policy R. As one of the Markovian properties, it can be shown that the g(R) is independent of the starting state i as the number of time periods N approaches infinity. Hence, $V_i^N(R)$ may be approximated by

$$V_i^N(R) \cong N g(R) + V_i(R) \tag{4}$$

where $V_i(R)$ can be interpreted as the effect on the total expected cost due to starting in state *i*. Thus, from Eq. (4)

$$V_i^N(R) - V_i^N(R) \cong V_i(R) - V_j(R)$$
 (5)

the term $[V_i(R) - V_j(R)]$ is a measure of the effect of starting in state *i* rather than state *j*. Substituting the linear, approximate relations of Eqs. (4, 5) into Eq. (3) leads to the recursive equation

$$g(R) + V_i(R) = C_{ik} + \sum_{j=1}^{M} p_{ij}(k) V_j(R)$$
 (6)

Equation (6) represents one of the M equations corresponding to the state i for i = 1, 2, ..., M.

When a system operates according to the Markov chain, there are needed (M+1) values of g(R), $V_1(R)$, $V_2(R)$, ..., $V_M(R)$ which satisfy the set of M equations of the form Eq. (6). Note that there are M equations and (M+1) unknowns; one of the unknowns, say $V_M(R)$, can be arbitrarily set to equal zero. Following a given policy R, the corresponding values of g(R), $V_1(R)$, $V_2(R)$, ..., $V_{(M-1)}(R)$ can then be obtained by solving the set of M simultaneous linear equations.

In principle, all policies can be enumerated to find the policy which optimizes the g(R). However, even for a moderate number of states and decisions, this enumeration

technique is cumbersome. A different approach called Policy-Improvement can be used to evaluate policies and find the optimal set of decisions without a complete enumeration. The mechanism of this algorithm is presented in the next section.

III. Computational Algorithm

The Policy-Improvement algorithm consists of two steps: the Value-Determination step and the Policy-Improvement step. These steps are described as follows.

(1) Value-Determination Step: For an arbitrary policy R_1 (with decisions $D_i(R_1) = k_1$, and the corresponding values of $p_{ij}(k_1)$, C_{ik_1} , and $V_M(R_1) = 0$), this step solves the set of M equations of Eq. (6), or

$$g(R_1) + V_i(R_1) = C_{ik} + \sum_{j=1}^{M} p_{ij}(k_1) V_j(R_1)$$
 (7)

for i = 1, 2, ..., M. Hence, values of the $g(R_1)$, $V_1(R_1), V_2(R_1), ..., V_{(M-1)}(R_1)$ are obtained under policy R_1 .

(2) Policy-Improvement Step: Using the above calculated values of the V's, find the alternative policy R_2 such that for each state i, $D_i(R_2) = k_2$ is the decision which optimizes $g(R_2)$, with

$$g(R_2) = C_{ik} + \sum_{j=1}^{M} p_{ij}(k_2) V_j(R_1) - V_i(R_1)$$
 (8)

That is, for each state $i=1, 2, \ldots, M$, find the appropriate value of k_2 such that

OPTIMUM
$$[g(R_2)]$$
 (9)
 $k_2 = 1, 2, ..., K$

In turn, let $D_i(R_2)$ be equal to the optimal value of k_2 , which defines a new policy R_2 .

Using the new policy R_2 , the Value-Determination step is repeated. This iterative procedure continues until two successive iterations lead to identical policies, which signifies that the optimal policy has been obtained.

If the expected long-run total discounted cost is of interest, the above algorithm can be used with a modification to the recursive equation Eq. (6). With a specified discount factor a, the recursive relation of Eq. (6) can be modified as

$$V_i(R) = C_{ik} + a \sum_{j=1}^{M} p_{ij}(k) V_j(R)$$
 (10)

for i = 1, 2, ..., M. Here, the $V_i(R)$ is the expected long-run total discounted cost of the system starting in state i and continuing indefinitely. The $V_i(R)$ can be evaluated in a similar fashion as computing the average cost.

A computer program is written to incorporate both the average cost of Eq. (6) and the discount cost of Eq. (10). The optimal policy is determined utilizing the Policy-Improvement algorithm. This BASIC program code is presented in Appendix A. A sample problem, adapted from Ref. 2 and presented in the next section, is used for testing purposes. The calculated results of both the averaged cost and the discounted cost are presented in Figs. 1 and 2, respectively.

IV. Sample Problem

For the purpose of testing the computer program, a sample problem is taken from Ref. 2 and summarized as follows.

The condition of a given system is inspected and classified into one of four possible states as shown in Table 1. It is also assumed that the state of the system evolves according to some known probabilistic transition matrix given in Table 2. After each periodic inspection of the system, a decision must be made as to which action to take: Decision 1 is doing nothing; Decision 2 is overhauling the system; Decision 3 is replacing the system.

In addition, the following assumptions are made:

- (1) When the system becomes inoperable (State 4) and replaced (Decision 3), the system is found to be in State 1 at the time of regular inspection. It is assumed that the total cost incurred when the system is in State 4 is the sum of a replacement cost of \$4000 and a cost of lost production of \$2000.
- (2) When the system is overhauled, the system is returned to State 2 (operable with minor deterioration) at the time of regular inspection at the end of next time period. The cost of the overhaul process is taken as \$2000 and requires one time period to complete.
- (3) When the system is in States 2 or 3, defective items may be produced during the following operating period. The expected costs due to producing defective items are \$1000 when the system is operable with minor deterioration and \$3000 when the system is operable with major deterioration.

(4) The total expected cost incurred per one time period depends on the state the system is in and the decision made. The total expected costs (the maintenance cost, the cost due to producing defective items, and the cost from lost production) are tabulated in Table 3.

The above information completed the necessary inputs to the computer program. Figure 1 presents the optimal policies and the expected average cost of the sample problem. As the result of the Markov Decision Process, an average cost of \$1667 can be expected when the policy is to do nothing when the system is found to be in States 1 and 2, to overhauling the system when it is in State 3, and to replace the system when it is in State 4.

In the second case, as presented in Fig. 2, an interest rate of 11% (or discount factor of 0.9) was assigned. However, with the same policy as in Case 1, a discounted cost of \$14,950 can

be expected if the system started in State 1, \$16,260 if it started in State 2, etc.

V. Summary

The Policy-Improvement algorithm using a Markov Decision Process is incorporated in a computer program and tested with a sample problem on a Hewlett-Packard 2647A terminal. This computer program is capable of finding the best maintenance policy with respect to an optimal long-run average cost or the long-run discounted cost for a system with known transition probabilities.

From the standpoint of management and operation, the algorithm provides a useful tool in obtaining an optimal maintenance schedule which gives the best return on capital invested.

Acknowledgment

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References

- 1. Bellman, R. E., and Dreyfus, S. E., Applied Dynamic Programming, Princeton University Press, Princeton, N.J., 1962.
- 2. Hillies, F. S., and Lieberman, G. J., Introduction to Operations Research, 3rd Edition, Holden-Day, Inc., San Francisco, Calif., 1980.

Table 1. States of the system

State	Condition
1	Good as new
2	Operable with minor deterioration
3	Operable with major deterioration
4	Inoperable

Table 2. Transition matrix of the system

State	1	2	3	4
1	0	7/8	1/16	1/16
2	0	3/4	1/8	1/8
3	0	0	1/2	1/2
4	0	0	0	1

Table 3. Total expected cost per one time period

		Decision	
State	1	2	3
1	0	\$4000	\$6000
2	\$1000	\$4000	\$6000
3	\$3000	\$4000	\$6000
4	_		\$6000

```
* * * * * INPUT INFORMATION * * * *
MSTATE
NDECISION 3
MAXTRIAL
        1.0
MAXIMUM
        0
DISCOUNT
        0
STATE
        DECISION TIE-BREAKER
        D(X) TIED(X)
        i 0
i 0
1.
2
                0
        í
3
               0
         3
LONG-TERM AVERAGE COST/RETURN= 1666.67
        POLICY
                VALUE
STATE
                ----
                1666.67
                 1666.67
        1.
 2
                 1666.67
 3
                 1666.67
 4
         3
```

Fig. 1. Expected average cost

```
* * * * * INPUT INFORMATION * * * *
MSTATE
NDECISION
           3
MAXTRIAL.
           1.0
MUMIXAM
           Ü
DISCOUNT
           11.1111
                    TIE-BREAKER
STATE
           DECISION
                      TIED(I)
1.
             D(I)
                      0
 1.
            1
                      0
 2
            1
                      0
 3
            1.
                       Õ
                                 * * * * * *
               FINAL RESULTS
                     VALUE
STATE
           POLICY
                       14948.6
            1
 1.
                       16261.6
 2
            2
                       18635.5
                       19453.7
 4
            3
```

Fig. 2. Expected discounted cost

Appendix A

Computer Program Listing

```
2 REM....
              EQUIPMENT MAINTENANCE POLICY
3 REM....
                    MARKOVIAN DECISION ALGORITHM
4 REM . . . . .
                                   ....REM
5 REM ....
6 REM....
10 DIM Irow(10), Jcol(10), Jord(10), Y(10)
11 DIM Dd(10),D(10),P(5,5,5),R(5,5,5),Sum(5,5),Tied(10),Q(5,5)
15 LONG A(11,11),X(10),Eps,Simul
16 INTEGER D, Dd, Trial, Tied
20 REM
          ..... BEGIN OF DATA LIST
100 REM..
                            ! ASSIGN I/O DEVICES
102 DATA 0,6
                            ! PRINTOUT OPTION
105 DATA 0
                            ! NUMBER OF STATES IN CONSIDERATION ! NUMBER OF DECISION ALTERNATIVES
110 DATA 4
120 DATA 3
130 DATA 0
                            ! MAXIMIZE COST/RETURN IF >=1
140 DATA 10
170 DATA 0,.875,.0625,.0625
180 DATA 0,1,0,0
190 DATA 1,0,0,0
200 DATA 0,.75,.125,.125
210 DATA 0,1,0,0
220 DATA 1,0,0,0
230 DATA 0,0,.5,.5
240 DATA 0,1,0,0
250 DATA 1,0,0,0
260 DATA 0,0,0,1
262 DATA 0,1,0,0
264 DATA 1,0,0,0
270 REM.....
                      COST/RETURN MATRIX ( R(I,J,K) ) ......REM
       DATA 0,0,0,00
280 REM
         DATA 0,4000,0,0
290 REM
300 REM
          DATA 6000,0,0,0
         DATA 0,1000,1000,1000
310 REM
320 REM
         DATA 0,4000,0,0
       DATA 0,4000,0,0
DATA 6000,0,0,0
DATA 0,0,3000,3000
DATA 0,4000,0,0
DATA 6000,0,0,1.E30
DATA 0,1.E30,0,0
DATA 6000,0,0,0
322 REM
330 REM
340 REM
350 REM
360 REM
370 REM
380 REM
... COST/RETURN MATRIX, Q(I,K)=(P(I,J,K)*R(I,J,K).REM
383 DATA 1000,4000,6000
384 DATA 3000,4000,6000
385 DATA 1E30,1E30,6000
390 REM.....395 DATA 0,0,0,0
                      TIE-BREAKER, TIED(I) .........REM
400 REM.....
                      INITIAL POLICY, D(I) .....REM
410 DATA 1,1,1,3
500 REM..... END OF DATA LIST ..... REM
                                                                REM
998 REM
```

1.000	REM GENERAL INPUT
1005	READ Ki,Ko REM ASSIGN READ/PRINT FILES
1015	ASSIGN "OUTPUT" TO #Ko
1020	IF Ki(=0 THEN 1190
	ASSIGN "INPUT" TO *Ki
	READ #Ki;Iprint READ #Ki;Mstate
	READ #Ki;Ndecision
	READ #Ki; Maxi
	READ #Ki; Maxtrial
	READ #Ki;Discount REM INPUT TRANSITION MATRIXREM
	REMFOR I==1 TO Metate
	FOR K=1 TO Ndecision
	FOR J=1 TO Mstate
	READ *Ki; P(I, J, K)
	NEXT J NEXT K
	NEVT T
	REM INPUT COST/PROFIT MATRIX
1105	FOR I=1 TO Mstate
	FOR K=1 TO Ndecision REM FOR J=1 TO Mstate
1115	
1125	
1130	READ #Ki;Q(I,K)
	NEXT K
	NEXT I REM INPUT TIE-BREAKER FLAGREM
1150	FOR I=1 TO Mstate
1155	READ #Ki; Tied(I)
	NEXT I REM INPUT INITIAL POLICYREM
	FOR I=1 TO Metate
	READ #5;D(I)
	NEXT I
1185	GOTO 1350 REMREM
	READ Iprint
	READ Mstate
	READ Ndecision
	READ Maxi
	READ Maxtrial
	READ Discount REM INPUT TRANSITION MATRIXREM
	FOR I=1 TO Mstate
	FOR K=1 TO Ndecision
	FOR J=1 TO Mstate
	READ P(I,J,K) NEXT J
	NEXT K
	NEXT I

1260	REM INPUT COST/PROFIT MATRIX REM
	FOR I=1 TO Mstate
	FOR K=1 TO Ndecision
	REM FOR J=1 TO Mstate
1280	REM READ R(I,J,K)
4200	REM NEXT J
	READ Q(I,K)
	NEXT K
	NEXT I
	REM
	READ Tied(I)
	NEXT I
	REMREM
	FOR I=1 TO Mstate
	READ D(I)
	NEXT I
	REMREM
	FOR I=1 TO Mstate
	FOR K=1 TO Ndecision
	IF Q(I,K)(>0 THEN 1425
	NEXT K
	NEXT I
	FOR I=1 TO Mstate
	FOR K=1 TO Ndecision
	Q(I,K)=0 FOR T=4 TO Manager
	FOR J=1 TO Metate
	Q(I,K)=Q(I,K)+P(I,J,K)*R(I,J,K) NEXT J
	NEXT K
	NEXT I
1410	REMREM
1420	
	GOSUB 10205 ! PRINT INPUT INFORMATION
1.430	
	REMREM
	Discount=1/(1+Discount/100)
	REMREM
	IF Iprint>0 THEN GOSUB 10410
	Trial=0
	Trial=Trial+1
	IF Iprint>0 THEN GOSUB 10510
2020	
	REM VALUE DETERMINATION
2070	FOR I=1 TO Mstate
	FOR I=1 TO Mstate K=D(I)
2090	FOR I=1 TO Mstate K=D(I) FOR J=1 TO Mstate
2090 2100	FOR I=1 TO Mstate K=D(I) FOR J=1 TO Mstate A(I,J)=-P(I,J,K)*Discount
2090 2100 2110	FOR I=1 TO Mstate K=D(I) FOR J=1 TO Mstate A(I,J)=-P(I,J,K)*Discount IF I=J THEN A(I,J)=1+A(I,J)
2090 2100 2110 2122	FOR I=1 TO Mstate K=D(I) FOR J=1 TO Mstate A(I,J)=-P(I,J,K)*Discount IF I=J THEN A(I,J)=1+A(I,J) NEXT J
2090 2100 2110 2122 2124	FOR I=1 TO Mstate K=D(I) FOR J=1 TO Mstate A(I,J)=-P(I,J,K)*Discount IF I=J THEN A(I,J)=1+A(I,J) NEXT J IF Discount=1 THEN A(I,Mstate)=1
2090 2100 2110 2122 2124 2125	FOR I=1 TO Mstate K=D(I) FOR J=1 TO Mstate A(I,J)=-P(I,J,K)*Discount IF I=J THEN A(I,J)=1+A(I,J) NEXT J IF Discount=1 THEN A(I,Mstate)=1 A(I,Mstate+1)=Q(I,K)
2090 2100 2110 2122 2124 2125 2130	FOR I=1 TO Mstate K=D(I) FOR J=1 TO Mstate A(I,J)=-P(I,J,K)*Discount IF I=J THEN A(I,J)=1+A(I,J) NEXT J IF Discount=1 THEN A(I,Mstate)=1 A(I,Mstate+1)=Q(I,K) NEXT I
2090 2100 2110 2122 2124 2125 2130 2140	FOR I=1 TO Mstate K=D(I) FOR J=1 TO Mstate A(I,J)=-P(I,J,K)*Discount IF I=J THEN A(I,J)=1+A(I,J) NEXT J IF Discount=1 THEN A(I,Mstate)=1 A(I,Mstate+1)=Q(I,K) NEXT I N=Mstate
2090 2100 2110 2122 2124 2125 2130 2140 2141	FOR I=1 TO Mstate K=D(I) FOR J=1 TO Mstate A(I,J)=-P(I,J,K)*Discount IF I=J THEN A(I,J)=1+A(I,J) NEXT J IF Discount=1 THEN A(I,Mstate)=1 A(I,Mstate+1)=Q(I,K) NEXT I

```
2150 IF Iprint>1 THEN GOSUB 10610
2170 GOSUB 5000
2180 IF Discount(1 THEN 2300
2190 G=X(Mstate)
2220 X(Mstate)=0
2300 IF Iprint>0 THEN GOSUB 10710
                        POLICY IMPROVEMENT .....REM
3010 REM.........
3020 FOR I=1 TO Metate
3025 FOR K=1 TO Ndecision
3026 Sum(I,K)=0
3030 FOR J=1 TO Mstate
3040 Sum(I,K)=Sum(I,K)+P(I,J,K)*X(J)
3041 NEXT J
3042 Sum(I,K)=Sum(I,K)*Discount+Q(I,K)
3054 IF Discount=1 THEN Sum(I,K)=Sum(I,K)-X(I)
3058 NEXT K
3060 E=Sum(I,1)
3070 Dd(1)=1
3106 FOR K=2 TO Ndecision
3110 IF Maxi>0 THEN 3150
3120 IF E<=Sum(I,K) THEN 3170
3130 E=Sum(I,K)
3140 Dd(I)=K
3142 GOTO 3200
3150 IF E>=Sum(I,K) THEN 3170
3160 GOTO 3130
3170 IF Sum(I,K)(>E THEN 3200
3190 IF Tied(I)>0 THEN Dd(I)=K
3200 NEXT K
3202 IF Iprint>0 THEN GOSUB 10810
3310 NEXT I
3320 FOR I=1 TO Metate
3330 IF D(I)(>Dd(I) THEN 3360
3340 NEXT I
3350 GOTO 10905
3360 IF Iprint>0 THEN GOSUB 11010
3362 FOR I=1 TO Matate
3370 D(I)=Dd(I)
3380 NEXT I
3390 IF Trial(Maxtrial THEN 2035
3410 GOTO 11110
5000 REM
5005 REM
          . . . . . FUNCTION SIMUL ( N,A,X,EPS,INDIC,NRC )
5006 REM
5007 REM
            INDIC=-1, COMPUTE THE INVERSE OF THE N X N MATRIX
5008 REM
            INDIC= 0, THE SET OF EQUATIONS A(N,N)*X(N)=A(N+1,N+1) IS
5009 REM
                      SOLVED AND THE INVERSE IS COMPUTED
5010 REM
            INDIC=+1, THE SET OF EQUATIONS A(N,N)*X(N)=A(N+1,N+1) IS
5011 REM
                      SOLVED BUT THE INVERSE IS NOT COMPUTED
5012 REM
5013 REM
            EPS =MINIMUM ALLOWABLE VAULE FOR A PIVOT ELEMENT
5014 REM
                 =AUGMENTED MATRIX OF COEFFICIENT, A=A(I,J)
5015 REM
            Α
5016 REM
```

```
5017 REM
              =NUMBER OF ROWS IN A
5018 REM
5019 REM
                =SOLUTION VECTOR, X=X(I)
5020 REM
5021 Max=N
5022 IF Indic>=0 THEN Max=N+1
5023 REM
                  . IS N LARGER THAN SO . . . . .
5024 REM
5025 IF N<=50 THEN 5031
5026 PRINT #6;" N IS GREATER THAN 50"
5027 Simul=0
5028 RETURN
5029 REM
5030 REM . . . . BEGIN ELIMINATION PROCEDURE . . . . .
5031 Deter=1
5032 FOR K=1 TO N
5033 Km1=K-1
5034 REM
5035 REM .
             . . . SEARCH FOR THE PIVOT ELEMENT . . . . .
5036 Pivot=0
5037 FOR I=1 TO N
5038 FOR J=1 TO N
5039 REM
5040 REM .
                   SCAN IROW AND JCOL ARRARYS FOR INVALID PIVOT SUBSCRIPTS
5041 IF K=1 THEN 5048
5042 FOR Iscan=1 TO Km1
5043 FOR Jscan=1 TO Km1
5044 IF I=Irow(Iscan) THEN 5052
5045 IF J=Jcol(Jscan) THEN 5052
5046 NEXT Jscan
5047 NEXT Iscan
5048 IF ABS(A(I,J))(=ABS(Pivot) THEN 5052
5049 Pivot=A(I,J)
5050 Irow(K)=I
5051 Jcol(K)=J
5052 NEXT J
5053 NEXT I
5054 REM
5055 REM
                 . INSURE THAT SELECTED PIVOT IS LARGER THAN EPS . . . . .
5056 IF ABS(Pivot)>Eps THEN 5062
5057 PRINT #6; " ABS(PIVOT)="; ABS(Pivot); " IS LESS THEN "; Eps
5058 Simul=0
5059 RETURN
5060 REM
                  . UPDATE THE DETERMINANT VALUE . . . . .
5061 REM . . . .
5062 Irowk=Irow(K)
5063 Jcolk=Jcol(K)
5064 Deter=Deter*Pivot
5065 REM
5066 REM
                 . NORMALIZE PIVOT ROW ELEMENTS . . . . .
5067 FOR J=1 TO Max
5068 A(Irowk, J)=A(Irowk, J)/Pivot
5069 NEXT J
5070 REM
```

```
5071 REM . . . . CARRY OUT ELIMINATION AND DEVELOP INVERSE . . . . .
5072 A(Irowk, Jcolk)=1/Pivot
5073 FOR I=1 TO N
5074 Aijck=A(I,Jcolk)
5075 IF I=Irowk THEN 5080
5076 A(I,Jcolk)=-Aijck/Pivot
5077 FOR J=1 TO Max
5078 IF J(>Jcolk THEN A(T,J)=A(T,J)-Aijck*A(Irowk,J)
5079 NEXT J
5080 NEXT I
5081 NEXT K
5082 REM
5083 REM
                   . ORDER SOLUTION VALUES (IF ANY) AND CREAT JORD ARRAY
5084 FOR I=1 TO N
5085 Irowi=Irow(I)
5086 Jcoli=Jcol(I)
5087 Jord(Irowi)=Jcoli
5088 IF Indic>=0 THEN X(Jcoli)=A(Irowi,Max)
5089 NEXT I
5090 REM
5091 REM .
            . . . ADJUST SIGN OF DETERMINANT
5092 Ich=0
5093 Nm1=N-1
5094 FOR I=1 TO NM1
5095 Ipi=I+i
5096 FOR J≕Ip1 TO N
5097 IF Jord(J) >= Jord(I) THEN 5102
5098 Jtemp=Jord(J)
5099 Jord(J)=Jord(I)
5100 Jord(I)=Temp
5101 Ich=Ich+1
5102 NEXT J
5103 NEXT I
5104 IF Ich/2*2<>Ich THEN Deter=-Deter
5105 Simul=Deter
5106 REM
5107 REM
            . . . END OF SUBROUTINE . . . .
5108 RETURN
5109 REM
10100 REM....
               10110 PRINT #Ko
10120 PRINT #Ko
10130 PRINT #Ko
10140 RETURN
10200 REM...
10205 COMMAND "M F H Hp-Ib#1"
10225 PRINT #Ko; TAB(10); "NDECISION "; Ndecision 10230 PRINT #Ko; TAB(10); "MAXTRIAL "; Maxtrial
10235 PRINT #Ko; TAB(10); "MAXIMUM "; Maxi
10240 PRINT #Ko; TAB(10); "DISCOUNT "; DISCOUNT
10250 PRINT #Ko; LIN(1); TAB(10); "STATE", " "; "DECISION", "TIE-BREAKER"
10255 PRINT #Ko; TAB(10); " I ", " "; " D(I) ", " TIED(I) "
```

```
10260 PRINT #Ko; TAB(10); "----", "
                                           _H__H_____H___H___H___H___H___H____H
10265 FOR I=1 TO Mstate
                                  ";D(I),Tied(I)
10270 PRINT #Ko; TAB(10); I, "
10275 NEXT I
10280 IF Iprint(2 THEN RETURN
                                              "," DECISION "," STATE
                                                                     ","PROBABILITY"
"," P(I,J,K) "
"," P(I,J,K) "
                                                         10312 FOR I=1 TO Mstate
10314 PRINT #Ko
10316 FOR K=1 TO Ndecision
10318 PRINT #Ko
10320 FOR J=1 TO Mstate
10322 PRINT #Ko; TAB(10); I, "", K, J, P(I, J, K)
10324 NEXT J
10326 NEXT K
10328 NEXT I
10330 PRINT #Ko; LIN(2); TAB(10); " STATE ", " DECISION "
10332 PRINT *Ko; TAB(10); "AT CURRENT", "AT CURRENT"
10334 PRINT *Ko; TAB(10); " STAGE ", " STAGE "
10336 PRINT *Ko; TAB(10); " ( I ) ", " ( K ) "
                                             STAGE ","COST/PROFIT" ( K ) "," Q(I,K) "
10338 PRINT #Ko; TAB(10); "----"
10340 FOR I=1 TO Mstate
10344 FOR K=1 TO Ndecision
10346 PRINT #Ko;TAB(10);I,"",K,Q(I,K)
10348 NEXT K
10350 PRINT #Ko
10352 NEXT I
10360 RETURN
10400 REM...
10410 PRINT #Ko; LIN(2); TAB(10); " * * * * INTERMEDIATE RESULTS * * * * *
10420 RETURN
 10500 REM..
 10510 PRINT #Ko
 10520 PRINT #Ko;" ..... TRIAL ="; Trial
 10530 RETURN
 10600 REM...
 10610 PRINT #Ko
 10640 FOR I=1 TO Mstate
 10650 FOR J=1 TO Mstate+1 STEP 4
 10660 PRINT #Ko; TAB(10); "A(";I;",";J;")=";A(I,J); "A(";I;",";J+1;")=";A(I,J+1);
10665 PRINT #Ko; "A(";I;",";J+2;")=";A(I,J+2); "A(";I;",";J+3;")=";A(I,J+3)
 10670 NEXT J
 1.0675 PRINT #Ko
 10680 NEXT I
 10690 RETURN
 10700 REM....
 10710 PRINT #Ko
 10720 IF Discount=1 THEN PRINT #Ko; TAB(10); "G
 10730 FOR I=1 TO Mstate
 10740 PRINT #Ko; TAB(10); "V("; I; ") = "; X(I)
 10750 NEXT I
```

```
10760 PRINT #Ko
10770 RETURN
10800 REM....
10810 PRINT *Ko;LIN(1);TAB(10); "STATE", "DECISION", "VALUE"
10820 PRINT *Ko;TAB(10); "----", "----", "----"
10830 FOR K=1 TO Ndecision
10840 PRINT #Ko; TAB(10); I, K, Sum(I, K)
10850 NEXT K
10860 RETURN
10900 REM....
                      10905 PRINT #Ko; LIN(3);
10910 PRINT #Ko; TAB(10); "* * * * * * FINAL RESULTS * * * * * * "
10915 PRINT #Ko; LIN(3)
10920 IF Discount=1 THEN PRINT *Ko; TAB(10); "LONG-TERM AVERAGE COST/RETURN="; G
10925 PRINT *Ko; LIN(2); TAB(10); "STATE", " "; "POLICY", "VALUE"
10930 PRINT *Ko; TAB(10); "----", " "; "----", "----"
10935 FOR I=1 TO Mstate
10940 K=D(I)
10945 PRINT #Ko; TAB(10); I, "; D(I), Sum(I,K)
10950 NEXT I
10955 GOTO 11210
11000 REM....
                          .....REM
11010 PRINT #Ko;LIN(2)
11012 FOR L=1 TO Mstate
11014 PRINT #Ko; TAB(10); "OLD-D(";L;")=";D(L), "NEW-D(";L;")=";Dd(L)
11016 NEXT L
11020 RETURN
11100 REM.....
11110 PRINT #Ko; LIN(3); TAB(20); "$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$
11200 REM..
11210 PRINT #Ko; LIN(5); TAB(20); "* * * * * END OF TASK * * * * *"
11220 COMMAND "M f h hp-Ib#1"
60000 END
```